09017232 刘晓臻_课程研学报告（二）

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一、构建查询需求

报告（一）中已经指出，原文档标题“Effective Online Knowledge Graph Fusion”作为查询，即使是在其本身的（35 篇）文档库中，有关联的文档也仅 3 篇。经过在学术搜索引擎中的查找，哪怕以排序结果的前 10 篇（其中有 7 篇无关）作为理想文档集，对标题中的词排列组合，也无法在 Google Scholar 搜索的前 100 名结果中找到理想文档集里有的内容！

因此，不能使用原标题和原文档库，否则本实验无法进行，因为最终各项评分结果都是 0！

报告（一）中还给出了另外一篇论文（原论文的引文）《Computing semantic relatedness using wikipedia-based explicit semantic analysis》，以及用它构建文档库和查询的结果，在此使用本篇论文的标题构建查询（能够在后续搜索中搜索到理想文档集里有的）如下（“queries.txt”）：

```
semantic relatedness
computing semantic relatedness
semantic relatedness semantic analysis
wikipedia semantic relatedness
semantic relatedness wikipedia based
semantic relatedness wikipedia based semantic analysis
relatedness wikipedia based
```

二、构建理想相关文档集

根据报告（一）中得到的结果，选用向量模型的 top10 文档作为理想相关文档集“ideal_docs.txt”如下：

```
WikiRelate! Computing semantic relatedness using Wikipedia
Indexing by latent semantic analysis
Overcoming the brittleness bottleneck using Wikipedia: Enhancing text
categorization with encyclopedic knowledge
Evaluating wordnet-based measures of lexical semantic relatedness
Extended gloss overlaps as a measure of semantic relatedness
Exploring unexplored contexts for semantic extraction from syntactic analysis
Centroid-based document classification: Analysis and experimental results
Corpus-based and knowledge-based measures of text semantic similarity
Feature generation for text categorization using world knowledge
Feature Generation for Textual Information Retrieval Using World Knowledge
```

三、选择搜索系统

选择 Google Scholar 作为搜索系统，对每个查询取前 100 个标题，得到查询结果在“query_results 文件夹下。”

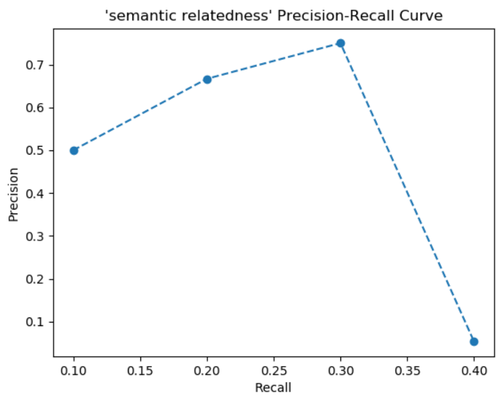
四、评价查询的检索效果

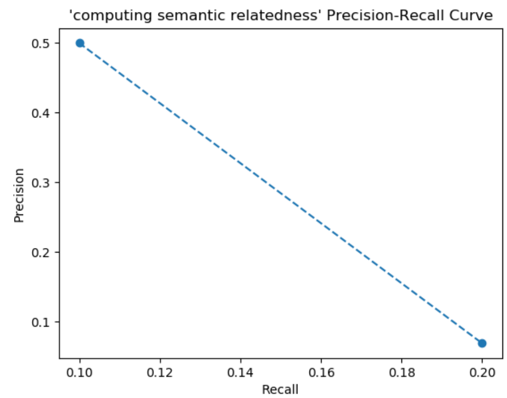
1. 每个查询结果集

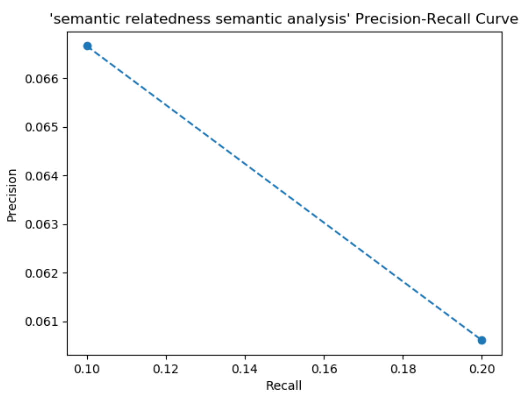
通过代码“evaluation.py”对每个查询结果集计算得到 Precision-Recall 对应关系及整个结果集的 Precision，Recall 及如“evaluation_results.txt”所示：

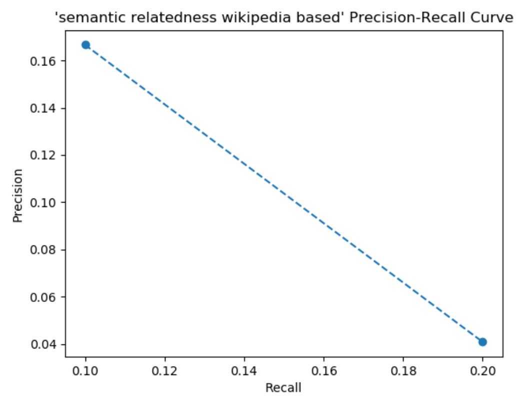
```
semantic relatedness:
{0.1: 0.5, 0.2: 0.6666666666666666, 0.3: 0.75, 0.4: 0.05333333333333334},
recall: 0.4
precision: 0.04

computing semantic relatedness:
{0.1: 0.5, 0.2: 0.06896551724137931},
recall: 0.2
precision: 0.02

semantic relatedness semantic analysis:
{0.1: 0.06666666666666667, 0.2: 0.06060606060606061},
recall: 0.2
precision: 0.02

wikipedia semantic relatedness:
{0.1: 0.5, 0.2: 0.02247191011235955},
recall: 0.2
precision: 0.02
semantic relatedness wikipedia based:
{0.1: 0.16666666666666666, 0.2: 0.04081632653061224},
recall: 0.2
precision: 0.02

semantic relatedness wikipedia based semantic analysis:
{0.1: 0.041666666666666664, 0.2: 0.029411764705882353},
recall: 0.2
precision: 0.02

relatedness wikipedia based:
{0.1: 0.5, 0.2: 0.038461538461538464},
recall: 0.2
precision: 0.02
```

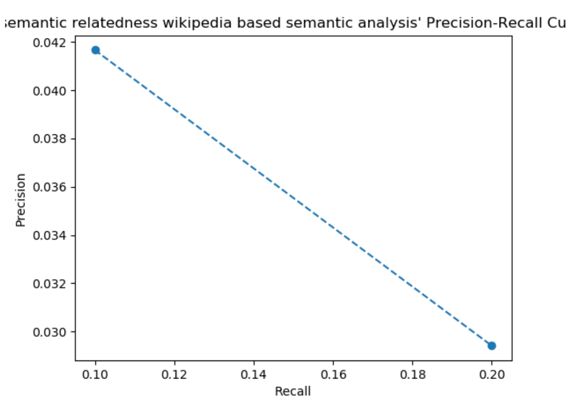
通过以上 P-R 对应关系，可以画出每个查询的 P-R 曲线如下（对应文件在 figures 文件夹里）：

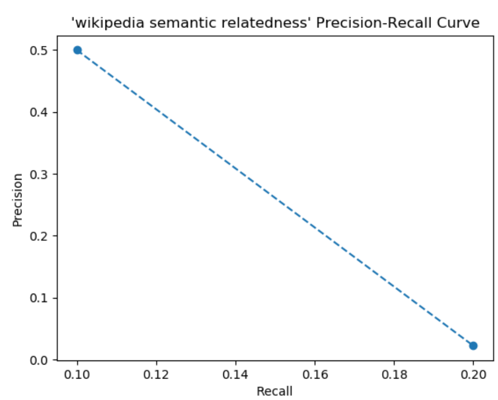

'semantic relatedness' Precision-Recall Curve
Precision
Recall

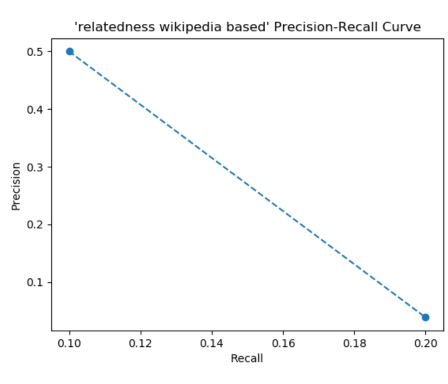

'computing semantic relatedness' Precision-Recall Curve
Precision
Recall


'semantic relatedness semantic analysis' Precision-Recall Curve
Precision
Recall


'semantic relatedness wikipedia based' Precision-Recall Curve
Precision
Recall


semantic relatedness wikipedia based semantic analysis' Precision-Recall Cu
Precision
Recall


'wikipedia semantic relatedness' Precision-Recall Curve
Precision
Recall


'relatedness wikipedia based' Precision-Recall Curve
Precision
Recall

2. 平均效果

同样使用代码“evaluation.py”里，计算出对于 q 的所有查询结果集的平均 Precision 为 0.022857142857142857，对于每个Recall值的平均Precision结果输出在“evaluation_results.txt”里。综上，可以画出平均 Precision-Recall 曲线“figures/avg_pr.png”，如下图。